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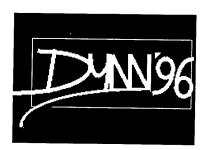
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dynamics of chaotic non-linear systems and their uses in image processing and pattern recognition, practical application of dynamic neural networks for VLSI implementation for image processing and pattern recognition.

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SESSION 1

Dynamics of Brain Organization

Principles of Brain Functioning

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There are presently attempts to build increasingly global models of brain function. This involves both the use of neuranatomy and neurophysiology, and leads to increasingly large simulations. In this talk some of the principles will be attempted to be extracted from these simulations and more general theoretical analysis of brain models and functions made so as to determine the general nature of brain processing. The talk will consider the posterior and anterior brain regions as involved in processes of global competition governed by the two systems of :

- a) the thalamus-NRT-cortex
- b) the frontal-basal ganglia-thalamus.

The modes of action of these will be outlined as :

- (i) concerned with running a global competition
- (ii) controlling actions taken on internal representations set up on active memory which may lead to new representations or to externally directed actions.

The first of these systems has been analysed extensively, and allows for an analysis in terms of a negative Laplacian net. The second goes under the heading of the ACTION network, and will be considered form the simulation and theoretical points of view. In particular the attractor structure and the nature of flows and mouldings of these attractors will be described.

The manner in which the ACTION network can support attention, active memory, template matching and other frontal features will be explained. At the other end of the spectrum is the nature of the neurons used, and the manner they will affect the global processing. This is particularly important if there are chaotic features, as seem to occur in EEG patterns in various cortical regions. The second part of the talk will describe the manner in which compartmental neurons can modify neuronal dynamics, especially during learning. Different topologies and connectivity patterns will be used to investigate the importance of intrinsic delays introduced by the compartmental neurons. Possioble catastrophic transitions in the parameter space will be described as related to interesting topological structures.

RST: a connectionist architecture to deal with spatiotemporal relationships

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keywords : Spatiotemporal processing, temporal neural networks, "Integrate and Fire" neurons, motion detection.

In the last decade connectionism has proven its efficiency in the field of pattern recognition. The next challenge is to do as well for spatiotemporal problems. Rather than improving any already known neural-network model, the aim of our work was to design and experiment an new connectionist architecture, biologically inspired and having abilities for spatiotemporal processing [2]. This model called RST is based on the two following principles:
 – taking **spatial** relationships (e.g. between neighboring pixels in an image) into account at the network level,
 – using a neuron model with **temporal** capabilities coming from biology.

Network

Concerning the spatial aspect, the network is placed in actual space (two or three dimensions), the metrics of which directly influence its structure through a connection distribution function. Following the arguments of Thorpe claiming that the information processing in precortical visual system should mainly be "feed-forward" [4], we choose for RST a "feed-forward" network.

A given number of neurons is randomly (with an uniform distribution) chosen among a portion of the considered space. Links are then created upon them according to their neighborhood: each neuron has a probability to be connected to a given previous neuron which is expressed in terms of the polar coordinates of the considered neuron with respect to this previous neuron. We choose to implement a generalization of layered models but keeping neighborhood relationships through a local connectivity. This local aspect is parameterized by an angle α outside which no connection is possible. The layered aspect is obtained by introducing a pick in the probability distribution. This pick corresponds to the average gap between layers. Notice that within this framework, a MLP network can be obtained by choosing α equal to $\frac{\pi}{2}$ and the standard deviation of connection probability much smaller than its mean (so as to get actual layers).

For practical reasons the portion of space among which the neurons are randomly set is delimited by two segments (rectangle areas in the 3D case) called "input" and "output" layers.

Each link between any two neurons is randomly weighted using an uniform distribution on a given interval $[w_{\min}, w_{\max}]$. If $w_{\min}$ is less than zero, we get inhibitory links in proportion $\frac{-w_{\min}}{w_{\max}-w_{\min}}$.

Neuron

The temporal aspect in RST is implemented at the neuron level [3]. Because it is close to biological models, easy to implement and fast to compute, we choose an "Integrate and Fire" neuron model with external refractory period and post-synaptic potentials (PSPs) modeling (see [5] for instance).

This model is basically described by two variables: a membrane potential V and a threshold θ. V is actually the sum of a specific potential U and the inputs sent by the connected neurons. Most of the time V is less than θ, but whenever V reaches θ, the neuron "fires". It sends a spike to the rest of the network it is connected to, and changes its state as follows: θ is increased by an amount $\Delta\theta$ and the specific potential U is lowered down to a post-spike value U_0. When the neuron does not fire, the two variables decay exponentially to their resting values U_∞ and θ_∞ with some time constant τ_U and τ_θ.

In addition to U and θ, another variable s is also introduced in order to reproduce the refractory period of the neuron. It is most of the time equal to 1 and drops down to 0 whenever the neuron fires. This so-called "shunt" function modulates the input received by the neuron, so that its membrane potential V is precisely: $V(t) = U(t) + s(t) \cdot E(t)$. After the neuron firing, the shunt function also decays exponentially towards its resting value 1 with the same time constant as U.

The input received by a neuron is the sum over space (all the inputs of the neuron) and time (all the firing instants of those inputs). We also include a model of synaptic transmission: the spikes sent by inputs of a neuron are actually received as PSPs (having a larger time scale than spikes).

Applications

RST has been applied to the spatiotemporal problem of motion detection in sequences of video images [1]. Consecutive images of a video sequence of people walking in front of static objects (e.g. doors) were presented one after another to RST input layer. The network parameters were set (once for all, without learning) so as to filter moving objects from static ones. The only firing neurons in the output layer were those corresponding to the moving objects in the input layer. The most important parameters of the architecture for this application appeared to be the mean of connection weights, the connection angle α and the standard deviation of the connection probability.

By this application and other experimental tests, RST has shown its straightforward ability —without learning — for spatiotemporal pattern processing. It should be emphasized that, because of its underlying principles, the output of RST directly has some topological meaning. There is no need for an external device to use the output in a spatiotemporal topological manner.

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Stochastic Activation Propagation in a Multilayer Network of Recurrent Clusters of Spiking Neurons

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This work comprises three stages.

1) First a recurrent cluster of spiking neurons is analysed qualitatively. These neurons have a probabilistic synaptic transmission and EPSC are extended in time and are modelled by alpha functions. Investigated clusters have typically 100 excitatory neurons, with random connections to 10% of the other neurons in the cluster, and to neurons in an input layer. The cluster as a whole responds with a high gain to specific input patterns and enters in an almost self- sustained firing mode. This response is characterized by a jitter in starting time, a latency, and a progressive decay of the activity when the input pattern is removed. These properties can qualitatively be reproduced by an abstract short-term memory (STM) neuron performing the coincidence detection of input spikes and exhibiting sustained firing.

2) A feedforward network of these STM neurons is analysed theoretically and by simulation. Analytical expressions are produced which relate latency to input jitter and level of activity [Bugmann and Taylor, 1994]. The network is provided with a feedback reset scheme which interrupts the sustained firing in lower layers once STM neurons in higher layers have recognised their input patterns, and are thus entering a sustained firing mode. Such a network can be used to model visual masking, where it predicts prolonged sustained firing in lower layers, as observed by Rolls and Tovee [1994]. The feedback scheme induces an oscillatory activity in the network, and predicts oscillations in the LGN controlled by V1, as observed by Sillito et al. [1994]. Time dependent post-stimulus histograms are observed, as in [Richmond et al., 1987].

3) It is explored, via a simulated model, how these dynamical properties can be are exploited in the design of a model for recognition driven visual saccade control. The model is a 2-stream artificial vision system inspired by the biological vision system. Several biological observations are at the basis of the system. - In area IT of the monkey, neurons are found which respond specifically to certain objects but independently on the position of the object in the visual field [Chelazzi et al, 1993]. This means i) that the object recognition process in the brain is location invariant and that a model such as the one proposed by Rolls [1994] is to be sought, ii) the firing of cells in IT identifies objects but does not tell where they are. Thereby, another system, for localisation, must be coupled to the IT stream. - All the neurons in area IT respond initially to their preferred object in the visual field, but if there is a specific object towards which the neuron should look, then only the neurons corresponding to that object stay active, all others becoming silent [Chelazzi et al, 1993]. This tells us that there is an attentional process which can control the activity of neurons in IT. However, a neuron being active does still not tell where the object is, so as to guide the eye movements. - Saccadic eye movements towards a point in visual space are controlled by neurons in the Superior Colliculus (SC). The model proposed here exploits the synchronization occurring in lower layers, due to the recognition process in higher layers, to tag object

locations in a way that can then be picked up by the parietal stream and/or eventually the SC to drive eye saccades.

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SESSION 2

Biological Systems : Vision

Temporal aspects of cortical processing in primate visual cortex

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It is usually assumed that information in the primate visual system is processed in serial or hierarchical fashion. Neurons of the lateral geniculate nucleus (LGN) which relay the retinal signals project almost exclusively to area 17, also called area V1. Area V1 constitutes the lowest level of a hierarchy of cortical areas of which areas V2, V3, V4 and MT constitute the successively higher processing stages. It is known that when area V1 is inactivated or lesioned, other cortical areas, such as V2, V3, V4, MT are silenced or their activity is strongly reduced. The serial model suggests that information is first processed within area V1, transferred to area V2 for further processing before being sent to areas MT or V4.

If this was the case, neuronal activity corresponding to a visual stimulus would travel through the visual cortex as a wave starting in area V1 and ending in the temporal and parietal cortices. Such a model of organization poses serious problems for the temporal integration of neural activity between neurons of the areas located at different stages of the hierarchy. Because of the slow rate of information transfer in axons of the cerebral cortex, feedback signals would come too late to act upon the incoming wave of activity. Another potential problem is related to the slow integration times of cortical neurons. Visual recognition can be done in 150 msec. Neuronal signals arrive in area V1 30 msec after the stimulus. If one estimate the average integration time of cortical neurons at 10 msec and the average conduction time between areas at 5 msec, one is left with 8 as the maximum number of processing stages before visual recognition is achieved, i.e. 1 neuron per level of the hierarchy (Thorpe and Imbert 1989)

Because of such difficulties associated with the serial model we have tested its plausibility by recording in areas V1 and V2 which constitute the first two stages of the cortical hierarchy. We measured the latencies of the responses of cortical neurons in areas V1 and V2 to flashes of light centered in their receptive fields to determine whether the responses of neurons in area V2 lag behind those of neurons in V1. The latencies of neurons in areas V1 and V2 are spread across a wide range (30 to 150 msec) and the latencies to visual stimulation of V2 neurons lag by about 10 msec behind those of neurons in V1 (Nowak et al. 1995) . A substantial part of this latency difference (5 msec) can be accounted for by conduction times in the axons between the two areas. If one assumes that cortical processing time is reflected in the latencies of cortical neurones, our data suggest that such processing is done in parallel in the two areas and a serial model appears very unlikely. This is further supported by the results of cross-correlation experiments showing that many neurons in areas V1 and V2 synchronize their firing and do not display characteristic patterns of neurons in area V1 driving neurons in area V2, as expected from a serial model of organization.

Comparison of published data in areas V1, V2 and MT also show that neuronal activity begins at the same time in areas V2 and MT, despite the fact that area MT is placed three levels higher than V2 in the hierarchy of cortical areas (Bullier and Nowak 1995) . Such data suggest that neural activity is simultaneous in most cortical areas beyond V1.

We have also investigated whether neural activation resembles a wave spreading through areas V1 and

V2. It is well established that visual information is relayed to the cortex of area V1 through two major channels, the M channel circulating through the magnocellular layers and the P channel through the parvocellular layers of the lateral geniculate nucleus. A certain amount of functional specialization is found among these channels : color information is carried almost exclusively by the P channel whereas high temporal frequency and low contrast information is transferred through the M channel. However, nothing is known concerning the way they interact during visual perception. We have addressed this question by measuring latencies to visual stimulation at different sites within areas V1 and V2 that are driven by the M and P pathways.

We found that neurons of area V1 driven by the M channel are activated 20 ms earlier than those of the P channels (Nowak et al. 1995) . This difference is important since it is twice the latency difference between successive stages in the hierarchy of cortical areas, like between areas V1 and V2.

In V2, neurons in the thick cytochrome oxidase bands, that belong exclusively to the M channel, and neurons of the pale bands, that are driven by M and P inputs, are activated 20 ms earlier than neurons of the thin cytochrome oxidase bands (Munk et al. 1995) . The consequence of the early latencies in the thick cytochrome oxidase bands is that their target, area MT, and the parietal cortex are rapidly activated by visual stimuli. Interesting speculations can be made of the latency difference between thin and pale cytochrome oxidase bands in areas V1 and V2. Neurons of the thin bands respond to low spatial frequencies, are often color-coded and can be thought of coding the surfaces of objects whereas neurons of the pale bands may be involved in coding the orientations and positions of edges. Since both the thin and pale bands project to V4 which acts as a relay in the ventral occipito-temporal stream that is involved in object recognition, our results suggest that information about edges of objects are transferred faster to temporal cortex than information about surfaces. The early firing of area V2 by neurons of the M pathway coding for edges may be also important in triggering activation of the feedback pathway from V2 to V1 that could mediate interactions in V1 with the delayed P information concerning surfaces.

What are the functional consequences of this difference in timing between the M and P channels at later stages of the visual cortex ? Neurons of area V4 receive information from neurons of the M and of the P channels, information that is transfered to the inferotemporal cortex which is important for pattern recognition. Modern hypotheses suggest that pattern recognition cannot be properly achieved by a purely "bottom-up" approach. Instead, it is supposed to involve a bidirectional process. A sketchy representation of a pattern activates the inferotemporal cortex that sends back signals through feedback connections corresponding to hypotheses concerning the representation of the pattern. This descending information is supposed to interact with incoming information arriving in extrastriate cortical areas. Such a scheme requires the presence of a system that provides the early sketchy description of the pattern. We propose that this corresponds to the neural activity carried by the M pathway into the inferotemporal cortex.

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The speed of processing in the human visual system : Implications for theories of visual computation

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Some recent experiments from our laboratory (Thorpe, Fize & Marlot, in press) have used Event Related Potentials to measure how long it takes for the human visual system to process complex natural images. Subjects had to decide whether a briefly presented colour photograph (presentation time 20 ms) contains an animal or not. Target images included a very large range of animals in their natural habitat (mammals, birds, reptiles, fish...) whereas the distractors included a wide variety of natural scenes (forests, lakes, mountains, flowers and fruit...). Despite the very severe challenge to the visual system posed by such a task (each image was only ever seen once, thus ruling out image specific learning) subjects performed remarkably well, averaging 94% correct with reaction times that varied from 380 to 580 ms. Even more surprising was the discovery that scalp potentials recording from frontal sites revealed a clear differential effect that distinguished between animal and non-animal stimuli at about 150 ms after stimulus onset, implying that the visual processing necessary to perform this task has already been achieved at this time.

Given the anatomical and physiological constraints imposed by our knowledge of the visual system, such data have major implications for theories of visual computation. In particular, they imply that the processing necessary for this task can be done on the basis of a feed-forward pass through the visual system. Furthermore, given the large number of layers of neurones involved it would appear that conventional firing rate codes would be too slow. An alternative hypothesis treats individual neurones as analog to delay converters. In such a case, rapid processing could be obtained by using the order in which neurones generate spikes as a code. Recent work indicates that this sort of spike order coding could well provide an important key to understanding the remarkably efficiency of the human visual system.

Neuronal Dynamic and Synchronization in the visual cortex

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The mammalian neocortex is subdivided into a number of functionnal areas. Each of them is connected to other cortical areas, and receive information from the sensory surface. Experimental studies have shown that cortical neurons activated by external stimulus could synchronize their spike trains. One important question concerning cortical synchronization is to determine whether it is mediated by thalamic inputs (which receive information from the sensory surface) or cortico-cortical connections (which receive information from other cortical area s).

A network architecture inspired from biology has been built. The neural net is composed of 4 layers of neurons. The first area models part of the retina, that receives images of the external w orld. Layer 2 models an intermediate area between the retina and cortical layers which receives informations from retina (LGN). Two opposite layers 3L and 3R model parts of Left and Right hemispheres in the visual cortex. This network corresponds to a monocular vision. Our network, like most biological networks, is not fully connected; the synaptic organization of the network is initially imposed, by biological constraints. The spatial distribution of connections is randomly chosen among layers, using u niform distributions.

A probabilistic model is proposed to model the behaviour of neurons. This model takes into account both spatial and temporal integrations with intern eural delays. Its own particularity is the model of the refractory period using for each neuron, a spike memory term, which sum up the spiking history of the neuron itself. Neuron states are binary {0,1}, and dynamic is stochastic.

Simulating a visual environment of moving bars on "the retina" leads, in our artificial neural network, to the emergence of synchronization between neurons of opposite layers, even if these neurons have been receiving information from others layers with different temporal delays. Mutually coupled oscillator cells belonging to different opposite layers emerge too.

Our simulations reproduce results of biological experiments which observe synchronization and oscillations between cells of the two oppposite hemispheres, activated by external stimulus. During these simulations, special connectivity between cells has shown to be an important parameter for the emergence of synchronization but the spike memory term introduced in our model is an important factor wich induces synchronization between cells in a neural network of spiking cells.

Different models have already been proposed in the litterature to explain synchronization or oscillations in the visual cortex.

In our model, oscillations between cells are not a consequence of the intrinsinc periodicity of particular neurons such as pacemaker neurons and synchronization between cells depends not only on well chosen delays between cells, but mostly on an internal parameter of spike memory.

SESSION 3

Networks Theories 1

On-line Training of Memory-Driven Attractor Networks

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Abstract

A continuous time, on-line training algorithm is presented, which learns to classify input patterns P in a Euclidean space $\mathbf{R}^m$ (or a Hilbert space) by attractors of a differential equation $dx/dt = F(x)$ in $\mathbf{R}^d$ (or a Banach space). These nets include simple one-layer adeline-like nets as well as many recurrent nets. The attractors can be quite arbitrary— fixed points, limit cycles, fractals, etc.— but the training algorithm requires that we know approximately where they are.

A time-varying $d \times m$ memory matrix M feeds an input pattern P of norm 1 into the activation level $x = MP \in \mathbf{R}^d$. We assume both x and M change simultaneously, according to differential equations of the following form:

$$\tau \frac{dM}{dt} = (y - g(MP))P^T,$$
$$\frac{dy}{dt} = -y + MP + I(t)$$

where g is the (vector) transfer function, and $I(t)$ is the training input, which may be turned on or off from time to time.

Then x, y satisfy the system

$$\frac{dx}{dt} = -x + y,$$
$$\tau \frac{dy}{dt} = -y + g(x).$$

This is independent of P, but the meaning of x depends on P. For sufficiently small time constant $\tau > 0$, the behavior of x is well approximated by:

$$\frac{dx}{dt} = -x + g(x) \equiv F(x).$$

It turns out that any finite set of patterns P_α can be reliably associated to given attractors $\mathcal{A}_\alpha$ for () provided that:

1

- the P_α are sufficiently close to being orthogonal;
- τ is sufficiently small;
- each pattern is presented sufficiently frequently;
- the training signal I_α presented at least once with P_α takes values in a convex set contained in the basin of attraction of $\mathcal{A}_\alpha$.

Analog Computation and Dynamical Systems

Hava T. Siegelmann

This talk describes a new interface between dynamical systems and analog computers. As opposed to previous models we do not apply some nature principles to the Turing model but rather start from nature-based, realizable chaotic dynamical systems and interpret their evolution as generalized computation.

By applying the basic computational terms --- e.g., halting, computation under resource constraints, nondeterministic and stochastic dynamics --- to dynamical systems, a nature-based computational theory will be developed.

Learning Mechanisms in Cognitive Systems

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The usual classification problem for which most of the neural networks have been designed is then to find synaptic matrices with which the network maps **inputs** of a prescribed sequence of **patterns** to **outputs** , through one, several or a continuous set of **layers** . One can use several results on control of nonlinear systems to obtain **learning algorithms** converging to some solutions of this problem, such as the **back-propagation formula** (which is nothing other than the **adjoint equation** in control theory). The mathematical structure of the space of synaptic matrices involving tensor products, we then obtain in the formulas describing the learning algorithms **pure tensor products** , whose entries are the products of the presynaptic and postsynaptic activities. This explains in a mathematical way the emergence of **Hebbian rules** in learning mechanisms of neural networks.

However, by looking only at static or asymptotic problems (mapping inputs onto outputs, or finding equilibria and more generally, attractors), the evolution mechanism is neglected and the **"real" time** used to model the neural networks is often replaced by artificial times. For instance, the **algorithmic time** , describing the iterations of a given algorithm, is often interpreted as a learning rule, although it may not be related to the time involved in the modeling of the network. Or, in the case of multi-layer networks, the layers of the network represent a second time scale.

By choosing the route used by most neural networks, one may bypass the basic question: **Why and How do synaptic matrices evolve?** and the basic answer: **To adapt to viability constraints through learning laws which are feedbacks** of the neural network regarded as a control system, associating at each instant with any signal a synaptic matrix allowing the adaptation to viability constraints.

In order to highlight this problem of adaptation to viability constraints, one can enrich the concept of neural network by embedding it into the class of **"cognitive systems"** which should be closer to some cognitive considerations than pure neural networks.

The aim of a cognitive system is to **adapt** to (viability) constraints imposed by the environment through a "recognition mechanism", and "action" and "perception" laws regulated by "conceptual controls" (which can be synaptic matrices).

The variables of the cognitive system are described by its state and a regulatory control, which we call **conceptual control**. The state of the system (henceforth called the " **sensori-motor state**") is described by:
* the state and the variations of the environment on which the cognitive system acts.
* the state of cerebral motor activity of the cognitive system, which guides an individual's action on the environment.

The regulatory control of the cognitive system is described by **an endogenous cerebral activity which**

is not genetically programmed, but acquired by learning and recorded in the memory . The purpose of this activity is to "interpret" (or "illuminate") the sensory perception of the environment.

A learning rule is then a set-valued map associating to each sensori-motor state of the cognitive system a set of regulatory controls allowing to adapt to the viability constraints.

One can characterize and study the learning mechanisms which allow the cognitive system to adapt to viability constraints, to prove the existence of a **largest learning mechanism**, and to build specific "heavy evolutions" obeying an "inertia principle".

SESSION 4

Spiking Neurons

Pattern Recognition with Networks of Spiking Neurons
(Extended Abstract)

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Abstract

Networks of spiking neurons can realize pattern recognition tasks by encoding the patterns in the synaptic strength of connections between neurons. We examine a system that receives as an input a linear combination of its stored patterns and outputs the coefficients of the linear combination. Both the input and the output are given in temporal coding, hence the computation is based on the explicit firing times of the input neurons and not on the more common firing rate of neurons.

The precise formulation imposes several constraints on the system, which can be only approximately fulfilled by biological neurons. By simulations we show that the above described approach can be nevertheless realized by biological neurons in a very reliable way, giving rise to a very simple and straightforward method for pattern recognition in biological neural systems.

Various types of neural networks are known to be suitable for pattern recognition tasks. Most of them work on the basis of firing rates and not of single firing events. However there exists substantial evidence that biological neural systems can perform certain computations on the basis of a few spikes. It is also known that the timing of such spikes can be very precise (see e.g. [Mainen 95]). We focus here on a system where the computation is based on single firing events. The inputs and outputs are represented as time-differences between firing times of certain neurons. One can distinguish two different approaches, depending on whether one stores the patterns in the delays ([Hopfield 95]) or in the weights of certain synapses. We focus here on the latter one, since in this model querying a mixture of those patterns and also learning appear to be easier explainable. The basic construction has been presented in [Maass 95]. It is based on a two layer network consisting of simple integrate-and-fire neurons. Our goal is to adopt this approach to biological realistic neurons and to investigate how reliable these neurons (with different types of noise, non-linear effects in the synaptic integration etc.) perform on this approach.

The basic idea of this model can be described as follows: Each neuron of the first layer forms some synaptic connection to each neuron of the second layer. The system has stored m patterns, each consisting of n components. It has n neurons in the first layer (the input neurons) and m neurons in the second layer (the output neurons). The patterns are stored in the weights of the synaptic connections between the two layers such that the weight for the connection from the ith input neuron to the jth output neuron represents the ith component of the jth stored pattern. The system receives as input linear combinations of the stored patterns in temporal coding, i.e. the time difference between the firing time of the ith input neuron and the time, when some "reference"-spike is produced, represents the ith component of the input vector. In the same fashion the output is encoded by making all output neurons fire, where the time difference between the firing of the jth output neuron and the reference spike represents the strength of the jth pattern in the input. We assume the existence of an additional input neuron u_0, which produces the reference-spike. In order to achieve the desired firing times of the output neurons, the following assumptions are made:

- the stored patterns have to be from some bounded interval: $x^\alpha \in [-K, K]^n, \alpha = 1, \ldots, m$ for some proper $K \in \mathbf{R}^+$ and have to be orthogonal, i.e. $x^\alpha \cdot x^\beta = 0$ for $\alpha \neq \beta$

- the initial segment of the initial rising part of the EPSP (respectively decreasing part in the case of an IPSP) can be described by some linear function. PSP's (postsynaptic potentials) describe the influence of the firing of the presynaptic neuron on the postsynaptic one. An excitatory (inhibitory) PSP increases (decreases) the postsynaptic potential thus making it more (less) likely that the postsynaptic neuron fires.

- the time difference between the firing time of any input neuron and the reference spike may not exceed a certain predetermined value.

- the weights of the connections from the input neuron u_0 to the output layer are chosen such that for each output neuron the sum over the weights of all incoming connections equals a certain predetermined constant. This guarantees that all output neurons will fire, such that the time difference between the firing times of the output neurons and the reference spike represents the output.

This model has several essential advantages: The whole computation can be performed by biological neurons in a very short time (approximately 10 ms). Since the output is encoded in the same fashion as the input one could imagine a sequence of such systems, which first recognize low-order patterns and later high-order patterns. Hence complex recognition tasks can be solved by systems in a time range which is known to suffice also for various neural system of animals and humans. In this model it is also very easy to process sequences of inputs, which makes it easy to examine the time dependency of the coefficients of the linear combination.

In order to find out how strongly this model depends on the abovementioned assumptions, we are making computer simulations with the neural simulation system GENESIS (see [Bower 94]). In addition we want to find out how biological neurons that are more realistic than simple integrate-and-fire neurons perform on this approach. The output neurons were modelled by several compartments such that each synaptic input to some output neuron is on a different branch of the dendritic tree of that output neuron. The advantage of remote synapses is that the linear range for the interaction is much wider than for synapses on one branch (this means that the influence of the various PSP's at a certain time on the potential of the soma simply sum up). Despite of the fact that PSP's in biological neurons do not contain linear segments they approximate a linear function for a short time (approximately 3 ms) very well. The scaling of the weights is a crucial point in our model, since large weights cause non-linear effects in the PSP's. If the weights are too small, then noise on the membrane potential or on the threshold will have a stronger influence. We were able to show that the system behaves within quite a wide range very stable and reliable despite of those constraints especially for the case that all stored patterns consist only of positive reals. In the case of negative components IPSP's must be used. Since the efficiency of an inhibitory synapse is usually lower than that of an excitatory one, the range of possible weights is smaller here.

Finally we observe that it is not necessary that the orthogonality-condition for the stored patterns is precisely fullfilled. If for example some related patterns are not pairwise orthogonal (e.g. $x^\alpha \cdot x^\beta > 0$ for related patterns x^α and x^β) then the presence of one of those patterns enhances the output for the other of those patterns, which appears to be also the case in certain biological systems.

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The Pulse Coupled Neural Network (PCNN) as an Algorithm for Image Processing

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It became apparent in the mid-1980's that none of the approaches to a successful automatic target recognition (ATR) system were working. The fundamental reason was that no one had any provable method, or algorithm, that could demonstrably handle the problem. A huge amount of time, effort, and money was put into ATR, yet the fundamental problem remained unsolved. The three steps to ATR were well known: 1. Segment the image into regions. 2. Compute features from the image regions. 3. Classify the regions by their features. This is elementary stuff that is done by living creatures of the most stupid variety, yet it eluded the legions of frustrated researchers for decades. Flys do it. Fish do it. Spiders do it, even little spiders.

The problem was that the basic algorithm did not exist. At least, that is, not in the research literature. It definitely existed in Nature. It was reasonable to go back and study what Nature did, find out what segmentation actually was, what features were, and not only how the classification worked but exactly what was classified in the first place. By discovering the concepts of the processing found in Nature, one could (if successful) then throw out the biological means and keep the method, i.e., the algorithm. So the idea was to look for the algorithm as it is found in Nature. What could be found in neurodynamical systems that would apply to the ATR algorithm?

The simplest neurodynamical system is a single neuron. The neural input from its synpatic fields is a time signal of filtered pulses at various and variable rates. It feeds an integrate- and fire pulse generator to make the output pulse train to other neurons. The neurons' leaky-capacitor structure of both the main body as well as the dendrites provides some very complex interactions among the input signals. The original pulse-coupled neural network is the Eckhorn linking field model. Its essential core is that the inputs come in two separate internal channels, not one, and that these two channels multiply each other to form the final voltage potential that drove the pulse generator.

Each neuron ordinarily generated a pulse train whose pulse rate increased with the strength of the synaptic field input. However, due to the second channel (also with its own synaptic field), when both channels were active the neuron could be forced to trigger its pulses in approximate synchronization with the nuerons feeding it. The neurons would then link up in the sense that they would all fire together in synchronous bursts. Since this could only happen if the neurons had roughly the same levels of input strengths, only those with similar inputs (think intensity grey levels in an image) would link up. The network performed grouping by similarity. This was a fundamental new thing in neural net theory.

It turned out that the artifice of requiring two channels and a tiny multiplier somewhere in the cell was not necessary. The standard cell model can do it. But to show this required the development of a new mathematical tool for functions of a matrix that let the function itself be written as yet another matrix. It only applies to small matrices, which in turn means it can only solve a very simple cell geometry. (It has to be a single cell with two inputs, and in addition the inputs had to be constant in time.) But it did allow inclusion of the integrate-and-fire pulse generator (which made it a coupled nonlinear pair of differential equations) and a good model of the synapses themselves, the shunting model.

The bottom line is an algorithm. Its parts are:

1. A pulse-generator, to transform an intensity image into a binary pulse image. The pulse rates increased with the intensity.

2. Pulse coupling, so neighboring cells could synch up if they pulsed at similar rates, i.e., were dirven by similar intensities.

3. Different cellular configurations, causing each cell type to have it own pulse pattern, or rhythm, impressed on its output pulse train and convolved with its inputs as well.

4. Pulse signal combination, done by the cell as a complicated function involving weighted products of all the input time signal from other cells and groups of cells.

All four parts are done by the same small, simple, nonadaptive circuit. The circuit, well within the capability of current electronic chip technology, could then be made as the core of a smart pixel array of arbitrary size, and turned out to be extremely fast. The first crude proof of concept chip, with eight cells in a row, ran at 1 megahertz. It was hard to make these chips run slow enough; they perferred the megahertzes. They still had a good dynamic range, still could perform their four tasks, and fit well with image applications.

Although only bits and pieces of the overall system have been investigated at this time, it is possible to look ahead and see how it can fit together. Here is how it could work: An input image is transformed into a pulsing image. Similar pixels group, similar groups also group (the PCNN can segment not only intensity regions but also extended intensity gradient regions), and each object in the scene generates its own characteristic time signal. These time signals are invariant against all the known geometrical changes due to the camera-scene geometry: translation, rotation, scale, perspective and out-of-plane rotations (distortions), and overall scene illumination. Each color, or spectra, is sensed by a different pixel layer as in a standard color video camera, but in the PCNN each color type has a slightly different pixel geometry. For example, the capacitances can be different for each color type. The the objects' time signals in each color are distinct. This is found to be true in the human retinal gangilion cells, which have different shapes for each color type. The signals in each color for each object are multiplied, fusing the time signals of the objects' pattern, texture shape and spectral hue into a single composite time signal. The signal goes to an adaptive classifier where it is correlated with a previously impressed reference signal, and the level of the correlation serves to identify the object.

Pulsed nets are intrinsically indifferent to space and time. They work in both domains equally well because (when the ultimate casue is identified) time causality and linking are due to the decay of the signals in the elementary capacitors of the cells, while spatial linking is due to the local dendritic interconnects among the cells.

What prevents the PCNN from being a full-up automatic target recognition system is that it needs something to compare its outputs to, a reference signal with which to correlate. This is the next phase of the research. Since the standard nonpulsed neural net theories have for the most part been deeply concerned with these adaptive classification techniques for decades, and since the PCNN is completely compatible with and complementary to these adaptive models, there is a large body of knowledge available for guidance in the next phase of this work. There are other methods, too, and if they are more appropriate there is no reason not to use them.

A large assortment of adaptive techniques are available. For example, the total time signal of an object can be re-broadcast back into the linking wave patterns making the components of the time signal in the first place, and adaptively encoded into the waves. This puts information about the whole object into each of its parts, as is done optically in holograms. Alternatively, different objects can encode each other's time signals in their linking wave patterns so that the presence of one can recall the other. Or, more simply, the entire neural adaptive process can be discarded and a digital time signal reference used instead.

There are good near-term benefits in the segmentation properties of PCNN's, and in the mid to long term the new algorithm has strong promise of solving fully the problem of how to make an automatic target recognition system that works.

Key Words: Neural networks, smart pixel arrays, data fusion, image processing.

Biographical note: Dr Johnson received his doctorate in physics at the University of Maryland in 1979, and joined MICOM in 1980 after a one-year NRC posdoc at Marshall Space Flight Center. He has published several papers in neural networks and optics, and has ten patents in those areas. He recieved an Army R&D Achievement award in 1984, and a one-year Secretary of the Army Fellowship in 1991-92 for research in optical computing, in Erlangen, Germany, where he began his work on pulse-coupled neural networks.

Time-Dependent Modulation of EPSP Allows Fast Access to Cortical Maps

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Cortical maps reflect a precise topographic neuronal organization where neighboring sites of maximum relative activity on the cortical plane correspond to nearby points in parameter space. Because in such cortical structures signal processing relies entirely on patterns of connectivity, cortical maps have been suggested to be computationally efficient. This fact is supported by recent quantitative studies performed in topographically organized primate visual areas, that is in V1, in the inferotemporal (IT) cortex, and in the superior temporal sulcus (STS), where cells discriminate different complex visual stimuli within 5 to 10 ms. Because firing rate has been shown to be rarely in excess of 1 spike in a 5-10 ms period in cortex, one of the key question is whether cortical maps can operate on the basis of single spikes in multiple input sources.

The neural operation particularly at stake within this context is the competition among neurons of the map for maximal response to a given stimulus. Such a competitive mechanism is of prime importance for adjusting the response properties of cortical units. Its realization in terms of single spikes has been formally expressed and shown to rely on a modulation of individual excitatory post-synaptic potentials (epsp) using a mechanism that should not affect the somatic membrane potential. Moreover, and to account for fast cortical processing, we advocate an inhibitory modulation so that input signals coming first are left nearly unaltered, while those coming later are much more attenuated, giving more importance to signals with short latencies. Candidate mechanisms for such a modulation are presynaptic inhibition and shunting inhibition, both of which has been described and suggested to operate in the central nervous system. Realization of this modulation takes advantage of a simplified normalization of the neuronal signals, an operation usually defined in terms of Euclidean norms, and thus difficult to justify biologically. Computer simulations of this architecture yielded processing times as short as 4 ms for the correct activation of a cortical map comprising 1000 neurons.

SESSION 5

Chaos & Dynamics of Neural Networks

A dynamical theory of attentiveness

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We discuss different levels of information processing in cerebral cortex. We show that information is embedded in the interspike intervals of single cells. There is also information content in the interaction between two neurons. However, it is only at network level that pattern discrimination and motion detection become possible.

We present a model cortex made of two interconnected layers. Each layer is a network of oscillators in interaction. the networks are in chaotic state. In this state the model cortex can not process information. However, if unstable orbits embedded in chaotic attractors are stabilized, the system may categorize patterns and detect motion.

DYNAMIC ATTRACTORS AND ATTRACTOR LOCKING: TOWARDS DEVELOPMENT OF TRAINING AND COMPUTATIONAL PARADIGMS

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Continuously processing sensory signals and generating behavioral responses, the brain is capable of self-sustained activity patterns across ensembles of neurons. These ensemble patterns allow for the generation of oscillations, such as neural patterns involved in walking and swimming rhythms, and are involved in recognition of sensed patterns as they occur. In addition, the brain can think and imagine for chosen periods of time. This extensive set of temporal capabilities is supported by a neural system architecture with an inherent ability to operate in the temporal domain and to generate self- sustained activity patterns for prolonged periods of time. We would ultimately like to capture the cogent temporal dynamics from biological neural systems in computational models, with the goal of building new computational paradigms that are powerful with respect to analysis and generation of temporal signals and patterns.

Dynamic neural network models are capable of producing prolonged self-sustained activity and pattern generation, with changes in activations continuing across a network over long periods of time. Activation patterns can be stable, with no changes, or can resonate with simple oscillations, limit cycles, or chaotic oscillations. With the modulation of a weight multiplier g, the dynamics can progress from simple to more complex patterns, including chaos (Doyon et al, 1993, 1995; Sompolinsky et al, 1988). There is a rich potential for computational paradigms that could take advantage of the self-sustained temporal dynamics and the dynamic attractors in neural networks.

In this paper, we explore dynamics that arises in neural network models and identify relationships and patterns that could be useful in computational paradigms that utilize dynamic neural networks. We present observations of the activation dynamics of single-layer recurrent networks, with random weights, as they progress from simple to complex activity patterns. We consider that a dynamic network paradigm could potentially be used for pattern classification, where different initial states would evoke different end-state oscillations, or different external inputs would modulate those oscillations, yielding pattern-to-oscillation maps.

We have explored situations in which an external stimulus - a pattern - is applied to a choatic network, and locks the network into a limit cycle attractor ("attractor locking") (Palmadesso and Dayhoff, 1995). Unique patterns then evoke different limit cycles, and could in principal be distinguished by the limit cycles that they evoke.

Networks with multiple dynamic attractors were developed from networks with only one observed dynamic attractor, using a weight modification scheme designed to increase the multiplicity of the dynamic attractors (Dayhoff et al, 1994). The goal of the training was to develop more than one dynamic attractor in the neural network, and to constrain the basins of the attractors so that a set of chosen initial states would be forced into different basins. The chosen states would not have to occur in the attractor of its basin. Successful training was done on a variety of networks, including a 10-neuron network that was trained with over 100 attractors. After training, most of the initial states evoked different oscillations in the network.

Dynamic neural networks have a tremendous flexibility possible in their basins of attraction, as demonstrated through a study of binary networks (Dayhoff and Palmadesso, 1995). We define the basin class capacity as the capacity of a set

of neural networks to exhibit a variety of different basin classes. Simulations show that the basin class capacity of a binary network with only 5 neurons has over a thousand classes, and the basin class capacity increases rapidly with increasing size of the network. This high capacity is computationally significant because it creates flexibility in how the basins of attraction can divide up all of the possible states. This division could ultimately be used in pattern classification or other computations, where the attractor reached could represent an answer. Since we aim to eventually have paradigms that allow adjustment and training of attractor basin boundaries, we have accomplished the first step towards this aim, to explore how many sets of basins and basin boundaries are possible with weight adjustments.

We have trained an a priori chosen dynamic attractor into networks with a feed-forward configuration that has a single recurrent loop from output to input layer (Lin, Dayhoff, and Ligomenides, 1995). These networks included time-delays and adaptive time-delay mechanisms. At each iteration, the network input was a segment of a trajectory and the network produced the values for the next position along the trajectory. The networks were trained on circle and figure-eight trajectories, and were able to eliminate noise when a noisy initial trajectory was supplied. These capabilities would be useful in robotic trajectory generation and in control applications.

Complex dynamics generated by dynamic networks has yet to be fully tapped for applications and computational purposes. Important issues remain to be resolved about dynamic neural networks before they can be fully understood and fully developed. These issues include (1) how the weights and interconnection topology determine the dynamic self-sustained activity of the network, (2) the number of attractors in the resulting network, (3) the boundaries of the basins of attraction, and (4) the training of attractors into a network. When these issues are resolved, we may then understand how the tremendous span of a network's dynamic activities can be used in computational paradigms suitable for pattern recognition, signal analysis and control.

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Learning in a chaotic neural network

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Chaos has become a popular issue in many different scientific disciplines. From biology to physics, some common features have emerged, showing that chaos may be a general phenomenon appearing in various fields including neural dynamics. Babloyantz's team has exhibited a chaotic behaviour in some parts of the brain. Freeman's investigations on the olfactory bulb of the rabbit showed that its dynamics was chaotic, and that recognition of a learned pattern is linked to a dimension reduction of the dynamics on a much simpler attractor (near limit cycle). Both addressed the problem of the use and utility of chaos for information processing purposes.

Some authors have described chaotic neural networks. These models range from some neurons to larger models. Besides, theoretical studies on chaos in (infinite-sized) random neural networks without learning have been performed in particular by Sompolinsky, Crisanti & Sommers. By studying a discrete time random neural network with assymetric couplings, our team showed their results could be extended to a wider class of neural networks. We are able to to determine the range of random weights for which the network is chaotic. We can also explain the various changes observed in the dynamical regime when sending static random patterns.

Recently, we have focused our study on the effects of learning in chaotic neural networks. We propose a Hebb-like learning rule to store a pattern as a limit cycle or strange attractor. We numerically show the dynamics reduction of a finite-size chaotic network during learning and recognition of pattern. We have obtained effects remiscient of Freeman's observations : we observe **a reduction of the dynamics by learning** .

We can interpret the dynamical behaviour observed during the learning phase on the basis of our previous theoretical studies. The main idea is to interpret learning as a motion in parameter space. This space is cut into several bifurcation manifolds. The crossing of these manifolds leads to drastic changes in the dynamics. Some important indications on their structures can be obtained, giving an interesting interpretation of learning : the learning dynamics is viewed as an evolutionary process, occurring under the "evolutive" influence of the pattern to learn. It leads the system close to the "edge of chaos", in a state where it is very sensitive to the presentation of the learned pattern. The response of the trained network is *specific* to this pattern.

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Temporal Segmentation in a Neural Dynamical System

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Oscillatory attractor neural networks can perform temporal segmentation, i.e. separate the joint inputs they receive, through the formation of staggered oscillations. This property, which may be basic to many perceptual functions, is investigated in the context of a symmetric dynamical system. The fully segmented mode is one type of limit cycle which this system can develop. It can be sustained for only a limited number n of oscillators.

The limitation to a small number of segments is a basic phenomenon in such systems. Within our model we can explain it in terms of the limited range of narrow subharmonic solutions of the single nonlinear oscillator. Moreover, this point of view allows us to understand the dominance of three leading amplitudes in solutions of partial segmentation which are obtained for high n. The latter are also abundant when we replace the common input with a graded one, allowing for different inputs to different oscillators.

Switching from a common constant input to one with fluctuating components, we find that noise facilitates segmentation. Using an appropriate noisy input activating a few oscillators at a time, an unlimited segmentation pattern can be generated.

SESSION 6

Biological Systems : Vision

NEURAL MODELING: MULTIPLE STRATEGIES

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Both single-cell and network level modeling studies have neurobiological relevance. The combination of different modelling strategies will be demonstrated. The dynamics of the olfactory bulb -OB- (the firstrelay center of the olfactory system) is the subject of the studies.

The rhythmic and arrythmic behavior of the OB occurs due to the excitatory and inhibitory interactions betweem mitral and granules cells. Systematic numerical bifurcation analysis showed that chaos occur in case of excitatory lateral connections between mitral cells. The associative memory character of the OB is also demonstrated.

Simulation of detailed multi-compartmental models of single mitral and granule cells have been done using morphological and physiological data. The morphological data used to characterize the basic structure of each cell types are: soma size, length of interbranch segments, diameter of branches, branching probabilities, and density of dendritic spines. Physiological data on the kinetics of voltage- and calcium-dependent ion channels are incorporated into the model. The rhythmic and bursting firing patterns, the role of the individual ionic currents, signal propagation through the different compartments of the cells are simulated.

Synchronized activities in networks may emerge due to both excitatory and inhibitory coupling.

Computer simulations have been done by the NEURON simulation program.

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A Stochastic Model for Interconnected Neurons. Application to the Role of Lateral Inhibition for Coding.

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Numerous models have been proposed to represent the collective activity of a biological neural network which consists in neurons linked by means of excitatory or inhibitory connections. In this paper, we make an attempt to model in a simple (but not too simplist) way an interconnected neural network which receives stationnary external stimulations.

This model was first studied in Cottrell (1992) in a special case where the connections are only inhibitory. It is based on a simple single neuron model called sandglass model.

At every moment, the state of each neuron is modelled by the **time until firing** , that is the time that is supposed to remain until its next discharge. This time flows like a sand glass until the spike emission. The external stimuli are taken into account by the fact that each neuron has its own frequency of firing, which is constant with respect to the time, but can differ from one neuron to another one. The inhibitory (or excitatory) effect suffered by a neuron when one of its neighbors discharges is modelled by a positive (or negative) delay which increases (or decreases) its state.

he mathematical and numerical study of the global state shows that for a given external stimulation, one can observe completely different behaviors, according to the values of the positive or negative delays associated with the inhibitory or excitatory connections. We show that the model exhibit two kinds of limit state. In the convergent case, the system is ergodic and all the neurons have a positive mean firing rate. In the divergent case, it appears some **activity maps** which look like the real ones that can be observed in real situations : some neurons are silent while the others are active.. The complete mathematical study was possible until now only when the connections are only inhibitory. In that case, one can characterize the values of the positive delay which produce a divergent map. In the general setting, we study the role of the parameters which quantify the strengths of the connections by numerical experiments.

In the last part of our paper, we concentrate ourselves on the role of lateral inhibition and we study it in the frame of the network composed of the glomeruli in the olfactory system of the insect for example, as in Piat (1994). We show that our model allows to get some glomerular map quite similar to the real ones which can be viewed as the system responses to an odor. We prove that the role of the inhibitory connections is to increase the contrast of the responses,and to improve the qualitative discrimination power of the system.

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THE EXTRACTION OF 'KEY FEATURES' FROM AN OLFACTORY SIGNAL BY AN ANALYTICALLY TRACTABLE MODEL OF THE GLOMERULAR SYSTEM

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The high degree of similarities between olfactory systems across the species is an incentive to attempt to build a generic model of the olfactory processing. The olfactory tract can be split into three levels: the receptor cells, the glomerular stage, where the signal is supposed to be processed (extracted from noise and stabilized) and a third stage where the long term memory processing seems to take place. The glomerular structure and the neuronal typology strongly suggest that the glomeruli are functional units, and it is hypothesized that their different activities form a glomerular image in response to the receptor cell activity generated by the applied 'odour'. According to a recent result of molecular biology, each type of receptor cells projects mainly into a single glomerulus. The dominant presence of an inhibitory neurotransmitter at this level indicates that the synapses are essentially inhibitory.

The formal system that we analyze is proposed as a model of the glomerular stage. The architecture chosen is coherent with the previously mentioned results from neurobiology. Trying to keep the model as simple as posible, we represent each glomerulus by a formal neuron, inter and intra glomerular connections are inhibitory, and there is a one-to-one excitatory connection between receptors and glomeruli; all delays and synaptic weights are assumed to be equal; synchronous dynamics is investigated.

This model leads to an in-depth understanding of the space of representation of the stimuli; because, in the deterministic case, steady-states are generally not 'fixed points' but cycles, the question of the nature of the 'glomerular image' in such a system arises. The analysis of the emergent code suggests an ability of the system to extract 'key features' in a complex and fluctuating signal from receptors, with an intrinsic robustness with respect to the noise present in the input signal.

The properties of the proposed model can be summarized as follows:
. (i) it computes with attractors, leading, as usual in such systems, to a 'contraction' from the input space to the output space;
. (ii) because the inputs alter the energy landscape, a given input may lead to several attractors, depending on the state of the network at the time of application of the input; . (iii) nevertheless, minima

of the 'energy landscape' are preserved if some features of the inputs are preserved; as a consequence, once the system has reached a steady state after the application of a given input, it stays in this state irrespective of the fluctuations of the inputs, provided the latter comply with specific conditions.

The properties of the model will be investigated an put into the perspectives of its biological relevance and of its engineering capabilities.

SESSION 7

Network Theories 2

Redundancy Reduction and Independent Component Analysis: Algebraic and Adaptive Approaches

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In the context of both sensory coding and signal processing, building **factorized codes** has been shown to be an efficient stratategy. In a wide variety of situations, the signal to be processed is a linear mixture of statistically independent sources. Building a factorized code is then equivalent to performing blind source separation. Thanks to the linear structure of the data, this can be done, in the language of signal processing, by finding an appropriate linear filter, or equivalently, in the language of neural modeling, by using a simple feedforward neural network.

In this contribution we discuss several aspects of the source separation problem. We give simple conditions on the network output which, if satisfied, guarantee that source separation has been obtained. Next we derive new algebraic solutions. Then we study adaptive approaches, in particular those based on redundancy reduction and maximisation of mutual information. We show how the resulting updating rules are related to the BCM theory of synaptic plasticity. Eventually we shortly discuss extensions to the case of non linear mixtures. In all this contribution we will take care to put into perspective our work with other studies on source separation and redundancy reduction. Details will be published elsewhere.

FOKKER-PLANCK EQUATIONS FOR NEURAL NETWORKS

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n recent experimental data, obtained with multi-electrode recording techniques, quite significative correlations between the firing times of one or several neurons have been found. This seems to indicate that precise spatio-temporal patterns play an important role in the neuronal coding of information.

The concept of synfire chains, proposed by Abeles in order to explain these correlations, has given rise to a large number of numerical studies, essentially based on simulations. The classical models of neural networks either have completely artificial dynamics (this is the case of spin-based models like the Hopfield model) -- and are therefore unable to account for precise firing timings -- or deal with spike-rates or activities -- and do not, therefore, provide any clue to spatio-temporal firing correlations.

Most studies on synfire chains are based on deterministic equations for the evolution of the depolarization potential, while firing is governed by a potential-dependent probability. The coupling with afferent neurons therefore involves precise firing times which may be obtained from a random generator. This kind of formalism is well adapted to simulations, but not at all to theoretical developments.

Starting from a description based on the internal states of a neuron (characterized either by the depolarization potential or as a refractory state), we present a set of stochastic equations which gives a complete description of the dynamics of the whole network. These equations are based on rather smooth assumptions and model the inter-neuronal coupling with the help of phenomelogical post-synaptic potentials. The model-dependant evolution equation for the depolarization potential and the phenomenological inter-neuronal coupling equation are complemented by a conservation equation for occupation probability of the neuronal state. This conservation equation is an extension of the classical Fokker-Planck equation.

This set of equations provides a frame for the discussion of neural network models. It should also offer a safe basis for theoretical studies on the stability or the coupling of synfire chains.

A neural network model based on temporal cross-correlations between neuronal responses.

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This paper describes a model architecture based on the hypothesis, first proposed by Von der Malsburg et. al [Marlsburg86], that temporally coinciding stimuli, in certain areas of the neocortex, are represented by correlated firing of neurons. The network, with an initially fully connected hidden layer, uses temporal cross-correlations between the activities of its hidden layer as a basis for mapping similar activities into subregions with limited overlap between different subregions. Each pair of units is coupled by an oscillator whose function is to test for (dis)similarity between the activities of the pair. The oscillator subsequently generates a reciprocal zero-one correlation length that defines the instantaneous level of cooperation/competition between the pair. Since the (dis)similarity matrix is computed before the application of a window-like non-linearity, it can be stated that the subspace spanned by the active hidden units, in the different subregions, corresponds to the space of the principal component eigenvectors of the input.

A primary objective is then to maximize the correlations between the activities of the units in a subregion in order to preserve, as much as possible, the internal structure of a given data pattern in the high dimensional space while discounting, to a certain extent, factors that may be irrelevant to recognition. Relevant features are uncovered by assigning, to each hidden unit, a non-linear function with a probability density distribution that slightly deviates from the normal (Gaussian) distribution. The motivation for this is based on the fact that, if one wishes to identify "interesting" features in some data, then it suffices to look for directions onto which projections are as non-Gaussian as possible [Fyfe94, Barlow90]. The complete response function is derived from the observation that neuron pairs often subtract their outputs, yielding characteristic window response functions. The height and width of each window (kernel) can be temporally altered by the value of the local (temporal) cross-correlation function, also referred to as the short-term memory (STM) of the hidden unit. The model neuron uses the dynamically computed STM to achieve averaging where data points are sparse and locality where data points are dense. In other words, each unit uses its STM to temporally (de)emphasize its role in extracting statistically significant features from the given multidimensional data. This operation also helps to sift and eliminate irrelevant noise since only relevant features are acknowledged.

In order to counter the inhibitory effect of its STM, each unit also has a positive feedback signal for self-amplification. A corresponding intrinsic significance of the STM is that of stability. The resulting interplay of recurrent inhibition and recurrent excitation (on presentation of a new example) allows subregions to coalesce, disintegrate or fluctuate in size while simultaneously feeding the (output) layer above. Both the input and output weights are updated in proportion to the average output response from the hidden local regions defined by the corresponding kernels (i.e., Hebbian learning). In order to eliminate the need to propagate the error derivatives from the output to the input layer, each hidden unit also attempts to match its input-driven bottom-up information, from the input layer, with its

corresponding vector of output weights. In this way, the output weight vector biases the input weight vector towards regions of the input that cause the greatest error at the output, since the magnitude of the output weight vector is proportional to its contribution in reducing this error.

Both sets of weights are trained together on a pattern by pattern basis. The input weights are updated by defining an objective function, one for each hidden unit, which is then minimized through gradient descent. The definition of the hidden (dis)similarity matrix through activity correlations together with the Hebbian-type (correlation-based) update rules led to the network simply being referred to as a correlation-based network (CBN). The completely feedward nature of the network renders it very attractive for implementation in parallel hardware. A scaly architecture is also described that eliminates the interconnect complexity in the hidden layer. The feasibility of the approach has been demonstrated with some simulation results.

SESSION 8

Applications to Real Systems

Smart Sensors using Pulsed Coupled Neural Networks for Focal Plane Image Processing

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An important difference between biological vision systems and their electronic counterparts is the large number of feedback signals controlling each aspect of the image collection process.

For every forward path of information in the brain, from sensor to comprehension, there appears to be several neural bundles which send information back to the sensor to modify the way the information is collected. In this paper we will examine the role of such feedback signals and suggest algorithms for intelligent processing of images directly on the focal plane, using feedback. We consider first what form these signals might take and how they can be used to implement functions common to conventional image processing with the objective of moving the computation out of the digital domain and place much of it on the focal plane, or analog processing close to the focal plane. While this work falls under the general heading of artificial neural networks, it goes beyond the static processing of signals suggested by the McCulloch and Pitts model of the neuron and the Laplacian image processing suggested by Carver Mead by including the dynamics of temporal encoding in the analysis process.

We will discuss the dynamic neural model and introduce the pulse coupled signal used as an information carrier. We examine the role of feedback control for imaging systems using intelligent error signals. We show how control signals based on local and global behavior of detectors can be used to provide a number of image processing technique on the focal plane. These include edge detection, dynamic range control, segmentation and motion detection. We examine dynamic range control using adaptive histogram processing and segmentation by adaptive histogram limiting with local area smoothing. Biological mechanism for image analysis suggest a type of adaptive histogram processing is possible. VLSI pulse coupled network models, using an integrate and fire mechanism, are examined for fast generation of a histogram like signals. This signal is used to control the gain and offset parameters of the camera. The reverse problem is examine adding local receptor field for image segmentation. Conventional image pre-processing usually includes histogram equalization to provide a uniform distribution of the pixel information. Histogram equalization at the sensor would maximize the information content of the data and provide uniform imagery for robotic control applications. An algorithm is developed, which allows feedback to be provided to the image collection system.

While change detection algorithms have been partially successful, many important task remain unsolved. We suggest solution to these problems may lie in mimicking architectures and algorithms used by biological systems. Pulsed oscillatory neural network design, based on biomemonics, is examined for application to these these problems and evaluated for application to image analysis and segmentation of multispectral imagery from the Satellite Pour l'Observation de la Terre (SPOT). Using biological systems as a model for image analysis of complex data, a pulse coupled networks using an

integrate and fire mechanism is developed. This architecture, based on layers of pulsed coupled neurons is tested against common image segmentation problems. Using a reset activation pulse similar to that generated by sacatic motor commands, an algorithm is developed which demonstrates the biological vision could be based on adaptive histogram techniques. Histogram processing includes dynamic range control, and when combined with smoothing filters, provides segmentation.

This architecture is demonstrated to be both biologically plausible and more effective than conventional techniques. Using the pulse time-of-arrival as the information carrier, the image is reduced to a time signal, temporally encoding the image, which allows an intelligent filtering using hypothesis feedback. This technique is shown to be uniquely suited to some multispectral/multisensor imagery.

Exploiting the Signal processing Properties of Dendritic Trees for Pattern Recognition by Networks of Silicon Neuromorphs.

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In most artificial neural networks, a synaptic connection between two units performs a simple, scalar weighting of the information transmitted. In real nervous systems, synaptic transmission is a much more complex process in that temporal transformations are performed. To begin with, the input signals are typically encoded in pulse trains, the pulses producing their effects on the postsynaptic cell with some delay, and with temporal filtering over widely varying time scales. The inter action between different input signals impinging upon a neuron is also a complex affair, depending upon electrical properties of the postsynaptic cell, as well as on the chemistry of receptors and second messengers. Leaving aside these chemical mechanisms, it appears that many important aspects of neural processing might be understood in terms of an electrical model of the neuron that takes account, the dendritic tree, and of the disposition of synapses upon it (Mel, 1994).

In order to study patterns of synaptic connection on the dendritic tree that could give rise to discriminative functions, we present experimental results obtained with silicon neurons, either singly or in small networks. VLSI techniques have been used to fabricate neuromorphs that incorporate the essential features of the "classical neuron", consisting of an artificial dendritic tree, and a leaky integrate-and-fire "soma" (Elias and Northmore, 1995). The dendritic branches are composed of a series of identical compartments each with a membrane capacitance, two programmable resistors representing the axial cytoplasmic and membrane resistances, and transistors emulating an excitatory and an inhibitory synapse. The excitatory synapses depolarize the compartment, while the inhibitory synapses hyperpolarize it. The synapses, when activated by brief pulses, generate impulse responses at the soma whose amplitude depends upon synapse proximity. (We are currently developing variable conductance synapses). Summation of these impulse responses above a threshold amplitude, cause the soma to generate output pulses, which can be routed, via high speed digital circuitry, to an arbitrary set of synapses on the dendrites of the same and other neuromorphs within a network. A range of programmable delays can be imparted to each pathway. The spike firing threshold of individual somata can be controlled by impulse activity originating within the network.

The neuromorphs exhibit the classical modes of signal combination by temporal and spatial summation. Thus two input spikes delivered at the same proximity to the soma but on different dendritic branches elicit twice the amplitude of impulse response as one input alone. With this linear mode of combination, adjustment of spike firing threshold allows a neuromorph to respond to net input frequency greater than some cutoff value. However, when two impulses activate neighboring synapses close together in time, their effects sum sublinearly. This occurs because a single synaptic activation drives the compartmental potential almost to the driving potential for the synapse; further synaptic activations contiguous in space and time therefore deliver lesser amounts of charge, with reduced effects accruing to the potential appearing at the spike generator of the soma. Although this saturation effect is readily obtained with our artificial synapses, the same effects may well occur in the dendritic branches of cortical neurons (Ferster and Jagadeesh, 1992). Whether linear or sublinear summation of synaptic inputs occurs depends to a

great extent up on the spatial arrangement of active synapses on the dendritic tree. Simultaneous activation of clusters of same-sign synapses promotes sublinear interactions, while juxtaposition of opposite sign, or dispersed synaptic sites promotes linear interactions. We have shown that synapse layout can be used for spike frequency selectivity, and coincidence detection (Northmore and Elias, 1996).

It seems likely that these properties of signal interaction on the dendritic tree could be exploited for the recognition of complex spatio-temporal patterns. The problem is how to find the appropriate patterns of connectivity and conduction delays to perform a given discrimination task. While it may be possible in certain cases to approach the problem by rearranging synapses to emulate weight changes, as for artificial neural networks, it is unlikely that the full capabilities of dendritic processing would be realized in this fashion. Our neuromorphic system allows one to try out various connections schemes, and procedures for generating them, ultimately for use in relatively large scale networks.

As an example of the use of dendritic tree processing, we present a network that discriminates pulse trains representing speech sounds. Vowel sounds were digitized and converted into several parallel impulse trains, as follows. A pulse in a given train was generated when the digitized waveform ascended across a fixed threshold level. The different trains representing a vowel sound activated the synapses of a set of 4-branch neuromorphs, the 1st stage units, which in turn connected with a set of output units. The objective was to achieve vowel recognition by the firing of the appropriate output unit. Connections from each input train to the different 1st stage units were selected so as to provide a partial discrimination between the vowels. Various criteria and procedures including genetic algorithms and "development rules" are being tried. The connections between the 1st and output layer are trained using a straightforward delta rule involving the mapping of notional weight strengths to a combination of synapse number and synapse position on the output dendritic trees.

The results showed consistent discrimination between 3 different vowel sounds. The auditory systems of animals presumably perform similar analyses upon spike train patterns, particularly with low sound frequencies, or low frequencies of amplitude modulation, where frequency tuning mechanisms of the ear are insufficiently discriminative.

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Application of the Missileborn Artificial Vision System (MAVIS) to Image and Signal Processing

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Several years ago, when we designed the ETANN chip, analog VLSI appeared to be the only feasible way to do high density neural computing. In the last five years, however, digital parallel processing chips capable of performing neural computation functions have evolved to the point of rough equality with analog in system level computational density. The Naval Air Warfare Center, China Lake has developed a real time, hardware and software system designed to implement and evaluate biologically inspired retinal and cortical models. The system is called the Missileborn Artificial VIsion System (MAVIS).

The hardware is based on the Adaptive Solutions Inc. massively parallel CNAPS system COHO boards. Each COHO board is a standard size 6U VME card featuring 4 CNAPS chips and a single controller in an SIMD configuration. Each CNAPS chip has 64 fixed point, RISC processors running at 20 MHz giving each COHO board a total of 256 processors with a theoretical through put of about 6 GOPS. The MAVIS system is designed to have multiple SIMD machines (MSIMD) each performing a different corticomorphic functions in parallel. The current system has three COHO boards integrated together for a total of 768 processors and about 18 GOPS of capacity. A COHO Companion Board is built to support a real time VSB interface to an imaging seeker and a NTSC camera. VME is used to communicate between COHO boards. System level software has been developed which allows a high level description of corticomorphic structures to be translated into the native microcode of the CNAPS chips. Corticomorphic structures are those with computational forms similar to the neural structures of the retina, LGN or visual cortex. Most standard image processing forms are compatible with this structure.

The MAVIS system is a real time hardware and software system designed to be shrunk into a volume compatible with air launched tactical missiles. Initial versions of the software and hardware have been completed and are being tested with various sensors including a missile seeker. We will discuss results obtained with the system for non-uniformity correction of infrared focal plane arrays and target detection in clutter.